International journal of Engineering, Business and Management (IJEBM)
ISSN: 2456-8678
[Vol-5, Issue-2, Mar-Apr, 2021]
Issue DOI: https://dx.doi.org/10.22161/ijebm.5.2
Article DOI: https://dx.doi.org/10.22161/ijebm.5.2.1

A literature review of various techniques available on Image Denoising

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Received: 04 Jan 2020; Received in revised form: 29 Jan 2021; Accepted: 19 Feb 2021; Available online: 20 Mar 2021

Abstract— *This paper provides a literature review of the different approaches used for image denoising. Various approaches are studied and their results are compared to provide a better understanding of the filters used to de-noise images. It is shown that how a single image is subjected to various denoising techniques and how it can react to those filters. Statistical and mean deviation techniques used by halder et al. (2019)[1] and CNN techniques used by zing et al.(2018)[2] are reviewed in detail to show how salt and pepper noise can be removed from the images. Each paper that is discussed here has explored the individual approach based on their research and the aim of this paper is to discuss all those approaches in a subsequent manner.*

Keywords— ***Image pre-processing, noise removal, image denoising, salt and pepper noise, noise filter, non-linear filters, median filter, deep learning for noise removal.***

I. INTRODUCTION

The term noise means unwanted signal. This unwanted signal usually occurs while an image is transferred from one source to another. Source here doesn't mean any explicit source. Sometimes, noise occurs even while capturing the image and this electronic unwanted signal is not limited to signal only. Videos are also affected when they are exposed to electronic transmission and produce noise. This noise generally depends on an explicit source and can also procure in form of grains.

In other words, image noise is the unexpected variation of colors or brightness in the images. This noise can be generated by an electronic noise in the path. It can be produced by digital camera, image sensors or circuitry of a scanner camera. Image noise is undesirable product of image or video capturing and is required to remove. Image denoising is the process of removing noise from images and is most important step in pre-processing techniques. The PSNR value in image processing is a block that computes the peak signal-noise ratio between two images. It is a quality measure where the higher the PSNR value, the better is the quality of the compressed or reconstructed image.

In this paper, various algorithms are compared to provide a better understanding of the algorithms at the root level and analyses the works of different researches using different algorithms such as mean and standard deviation[1], deep learning techniques[2,3] such as CNN, iterative grouping median filter[4] and non-linear filters[5]

Each paper that is discussed here has provided an individual approach based on their research and the aim of this paper is to discuss all those approaches in a subsequent manner.

1.1 Salt and pepper noise:

Salt and pepper noise is the most common and major type of noise occurring in images. In this type of noise, images are seen with sudden and sharp disturbances. The intensity of the pixels of the images obtain either the highest or the lowest (255-0) values. 255 for white and 0 for black in case of black and white images[1]. This sudden change in intensity causes the depreciation in the quality of images. Hence, they are needed to be removed. To start with digital

color images, non-linear filters are used over time to remove salt and pepper noise from images and videos.

II. NON-LINEAR FILTERS FOR DIGITAL COLOR IMAGES

Digital color images is presented using a 3D matrix of RGB color where the first dimension reserves the red color, second dimension reserves the green color and the third dimension reserves the blue color[6]. Here, the intensity of each color ranges from 0 to 255. According to sharad J. et al[5], the quality of the digital color image depreciates from the moment it is captured. During the pre-processing and processing, the digital image is subjected to many kind of distortion from the moment it is captured to moment is stored. While the phase of image transmission and storing, an impulse noise is added to the images which affects the color image during this phase. Salt and pepper noise is a type of impulse noise which corrupts the image. When the image is affected, the pixels take either the higher value, 255(salt noise) or the lowest value, 0(pepper noise). Linear methods are not found effective to correct the salt and pepper noise so nonlinear filtering methods are used. These methods provide good quality de-noised image by increasing peak signal to noise ratio (PSNR), depreciated mean square error (MSE) and increased correlation between the original and the de-nosed image[7].

2.1 Median Filter:

In a median filter, a 3x3 matrix is taken which contains the intensity values of the pixels, as shown in the figure 1. The middle pixel is considered to denote the noised filter. This noised pixels value is corrected to the median value of all the pixels in the matrix and replaced with the median value. Standard Median filter is one of the simplest and the most frequently used non-linear filter but this algorithm might not remove the salt and pepper noise from images containing high image density ratio[1]. Over the years many modified median filters are introduced such as weighted mean filter (WMF) [8], center weighted median filter (CWMF) [9], detail-preserving median filter (DPMF) [10], recursive median filter (RMF) [11], switching median filter (SMF) [12], Alpha trimmed median filter (ATMF) [13] etc. In later years, more advanced median filters have been proposed including Fuzzy Switching Median Filter (FSMF) [14] , Adaptive fuzzy switching median filter (ASMF) [15] , Fast detection median filter (FDMF) [16] , Un-symmetric trimmed median filter (UTMF) [17] etc.

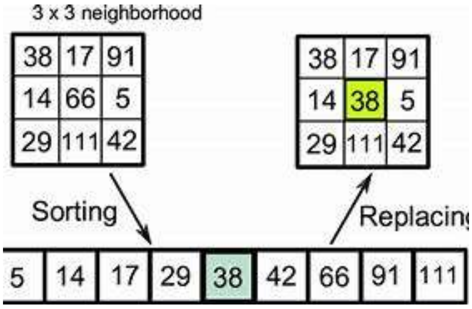

Fig.1: Median filter

In the algorithm proposed by halder et al.[1] the range of intensities that suit the intensity of the window is found out. The size of the local window is remained constant and not changed and it is checked that the calculated intensity can be used to change the impulse point or not. For this process, statistical mean and statistical median deviation is used.

2.2 Average Filter:

Average filter is another non-linear filter used to remove the salt and pepper noise. A mask of variable dimension is used to convolute with the noise image to reduce the salt and pepper noise in the corrupted image[5].

OCR (optical character recognition) is a technique that enables to detect the text contained in an image but in order to get good results, it is required to pre-process the image to remove noise contained in letter images. This can achieved by combining median and average filters[18].

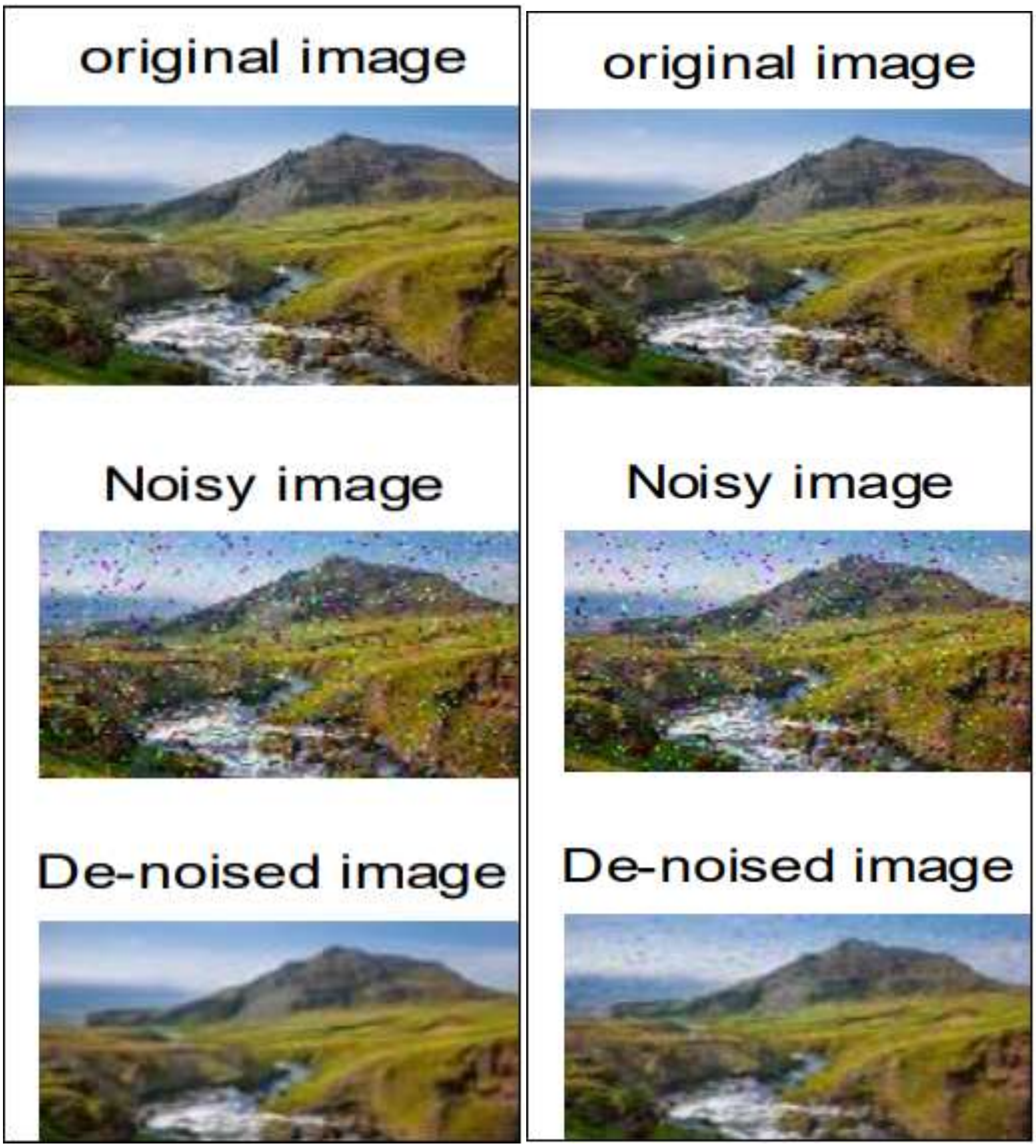

Fig.2: MF implementation (left), AF implementation (right)

2.3 Adaptive frequency median filter (AFMF):

As said by halder et al.[1] standard median filter s only limited to low density SPN, erkan et al. developed a new algorithm adaptive frequency median filter AFMF. This method is proposed by erkan et al[19] where a frequency median and adaptive frequency median filter is introduced. It was proposed that the AFMF uses the same adaptive condition as adaptive median filter AMF and the proposed frequency instead of the traditional standard median filter. According to the proposed algorithm, the frequency median calculates the new grey value for the centre pixel in the median filter and excludes the noisy pixels and only focuses on the uniqueness of the grey value, hence providing more efficient results than AMF [19].

III. DEEP LEARNING METHODS FOR IMAGE DE-NOISING

Deep learning in image denoising is a revolutionary topic gaining much attention. There are various deep learning techniques used for denoising process but their subsequent difference those techniques dealing with image denoising.

A brief overview of deep learning techniques is provided by Tian, C., Fei, L., Zheng, W., Xu, Y., Zuo, W., & Lin, C. W. (2020) [21] where more than 200 papers are reviewed for their contributions in image de-noising field. The main contributions can be summarized as follows:

1. Illustration of the effects of deep learning techniques in the field on image de-noising.

2. Summarization of the solutions of deep learning techniques for various noises (additive white noise, blind noise, real noise and hybrid noise).

3. Quantitative and qualitative analyses of the performance of noise removal algorithms in deep learning.

4. Characterizing potential challenges and directions for deep learning in the field of image denoising.

3.1. Machine learning for image de-noising:

There are supervised, semi-supervised and unsupervised learning methods in machine learning for noise removal. In supervised methods given labels are used and the obtained features are put closer to the target for learning parameters and the training the denoising algorithm[22,23]. In unsupervised learning methods, instead of label matching, training samples are used to find patterns and finish specific tasks such as un-pairing low resolution images[24]. For semi-supervised learning methods, a model is built and applied to construct learner to label unlabelled samples from a given data sample[25].

3.2 Operational Neural networks for image denoising:

Neural networks are the basis of all machine learning algorithms which are the basis for deep learning techniques[27]. Most of the neural networks consist of neurons, input X, activation function f, weights W = [W0, W1, … , Wn−1] and biases b = [b 0 , b 1 , . . . , b n]. A deep neural network is one which has more than three layers in it. However, it is difficult to implement these neural networks and require a good deal of manual settings to obtain desired results. Due to this, deep convolutional neural networks (CNNs) were proposed[28].

3.3 Convolutional Neural Networks (CNNs) for noise removal:

Convolutional neural networks have recently been adapted as the most favoured technique for image denoising due to its adaptive learning ability with a deep configuration. Deep CNN can be used to directly remove SPN from the images[20]. They use Convolutional neural networks CNN to directly remove noise from images. They used a multi-layer structure in CNN containing padding, batch normalization and rectified linear unit to remove salt and pepper noise from images. They divided the images into three sets- training set, validation set and test set. In their study, it was found that the model was able to remove salt and pepper noise from various images. Additionally, they were able to remove high-density noise as well due to extensive local receptive fields of deep neural networks. However, it was also found that their architecture was only able to perform on images with large number of interference pixels. Hence, their application was generalized for the removal of salt and pepper noise and produced competitive results. Definitely deep CNNs have attracted much attention but they don’t come without their limitation: (1) to train a deep CNN for denoising is very difficult, (2) most of the deep CNNs suffer a performance saturation situation[26].

IV. COMPARATIVE ANALYSES

So far this paper has discussed various methods and techniques that are used to remove noise from images. Now a comparative study is given which illustrates which methods fits to what situations.

Table 1: deep learning techniques for image de noising:

Methods	Applications	references
CNN	Additive white Gaussian and salt and pepper noise	Wang, Zhou, and Cheng (2020)[29]
CNN	Additive white Gaussian-poisson noise	Chen, Song, and Yang (2016)[30]
CNN	Additive white Gaussian noisy video	Davy, Ehret, Morel, Arias, and Facciolo (2018)[31]
CNN	Additive white Gaussian noisy video	Tassano, Delon, and Veit (2019)[32]
CNN	Blind video denoising	Ehret, Davy, Morel, Facciolo, and Arias (2019)[33]

Table 2: PSNR value of the various noise density 20-80% using ATMF, FDMF, AFMF, UTMF, FDMF, MF and SMF filters.

noise density ->	0.2	0.4	0.6	0.8
AMF[19]	26.33	23.23	21.16	17.35
AFMF[1]	33.79	31.28	26.68	25.68
ATMF[1]	34.47	28.55	21.67	14.26
FDMF[1]	34.74	30.39	26.82	22.84
UTMF[1]	34.8	30.34	26.51	19.55
MF[19]	27.43	18.54	12.17	8.02
SMF[1]	28.6	25.67	20.63	14.26

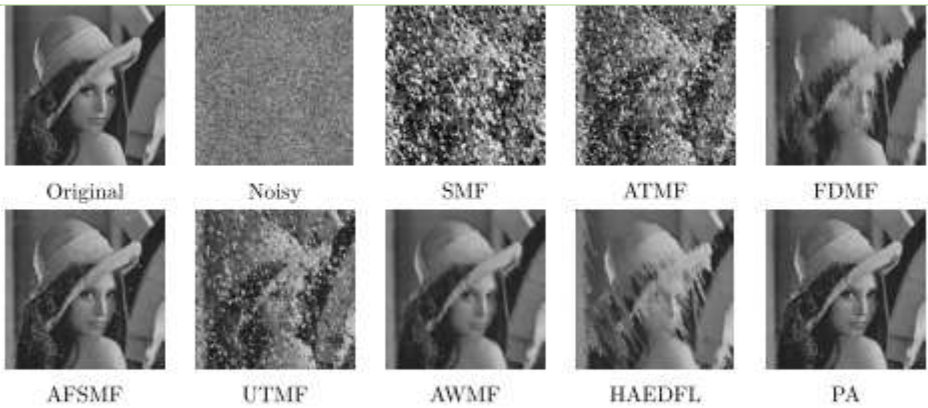

Fig.3: Quantitative analysis of an image with 90% noise density[2]

V. RESULTS AND CONCLUSION

Several results can be derived from ziad et al[7] which can be summarized as: (1) while apply de-noising algorithms, it is better to de-noise each color alone and OCF is better to remove salt and pepper noise density greater than 0.1[7] and average and median filters are considered bad to remove salt and pepper noise for low and high density noises. The method proposed by halder 2019 is specifically iterative in nature and can only replace noisy pixels under adequate conditions which is that at least a minimum number of neighbor pixels satisfy the algorithms the conditions stated in their paper. Also, the algorithm takes a fixed size window and their size depends only on experimentally calculated pre-defined threshold.

Below is a graph showing the comparison between the PSNR values of a image when subjected to different filters.

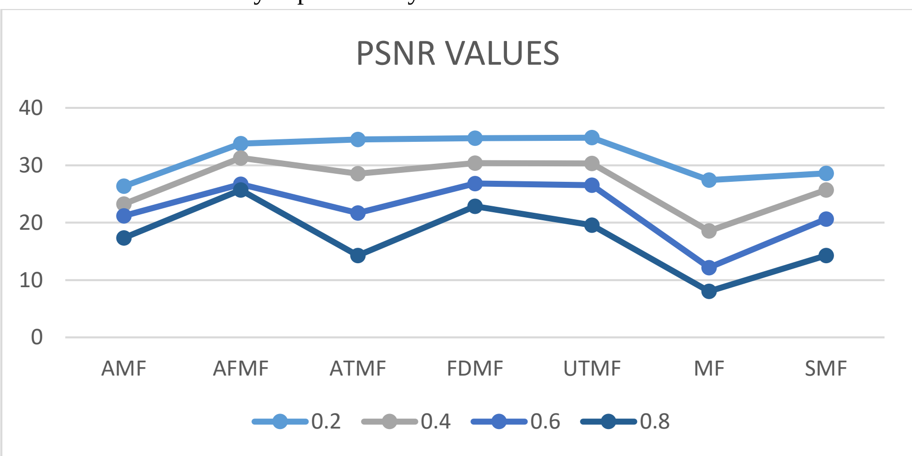

Fig 4. Comparison of PSNR values using different filters from table 2

This paper also discussed the deep learning techniques to remove noise from image. However, there are certain limitations observed while applying these methods in the field of image de-noising[3]: (1) More memory structures are required for deep learning techniques, (2) there is a lack of data when it comes to real noisy images as they are not easy to capture, (3) it is difficult to solve unsupervised de-noising tasks using deep CNNs. Gaussian noisy image de-noising have been quite successful over the few last years but in real world, real noises are more complex and irregular. On the other hand, Gaussian de-noising performs better is noise is regular. Nevertheless, deep learning tactics require the ground level truth when comes to de-noising algorithms and it's hard to obtain due to the difficulty that real noisy images are hard to capture, hence the ground truth is not fully prevailed. Therefore, there are sudden challenges that researched need to address in order to provide better algorithms for de-noising images.

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